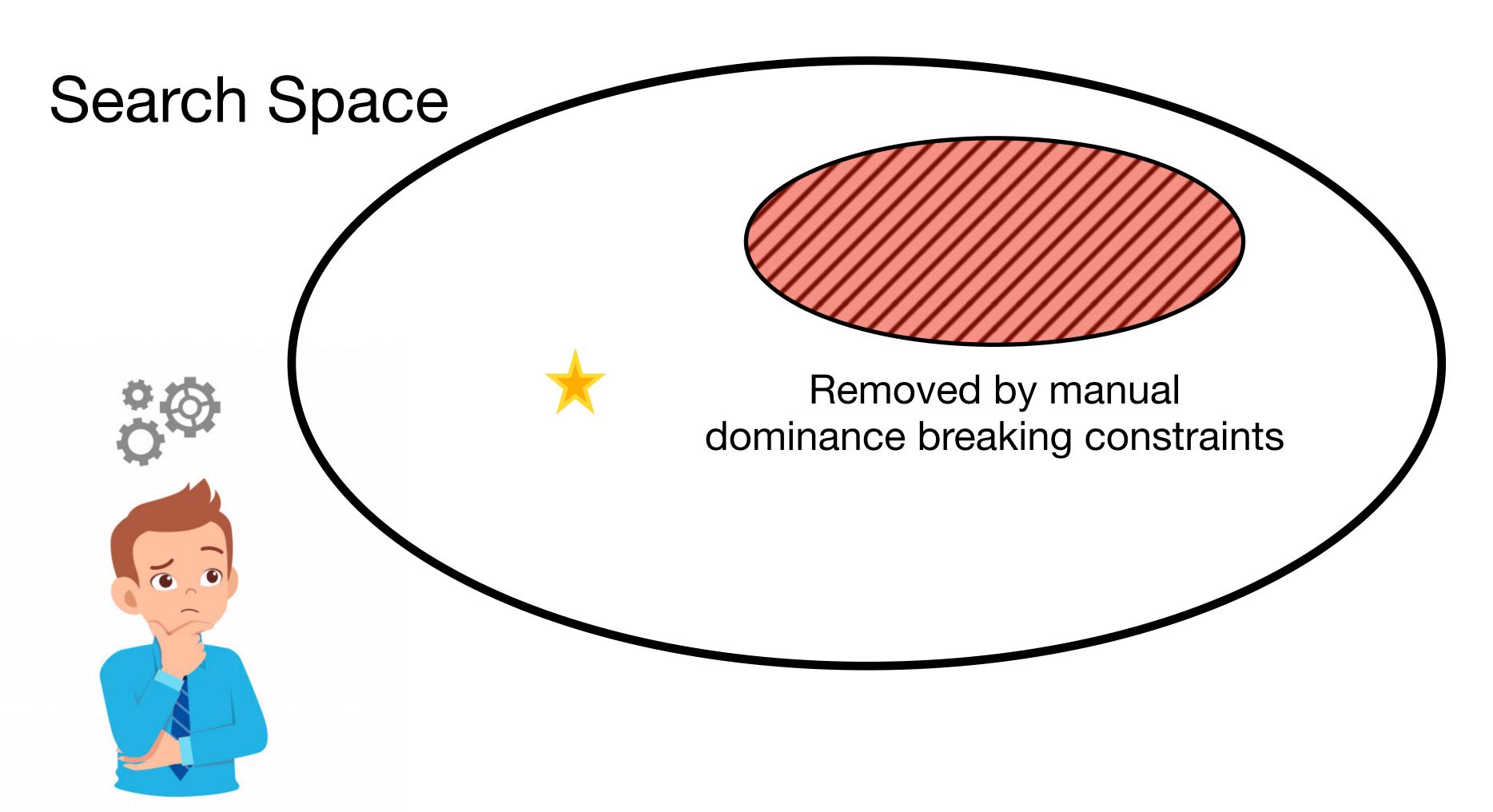
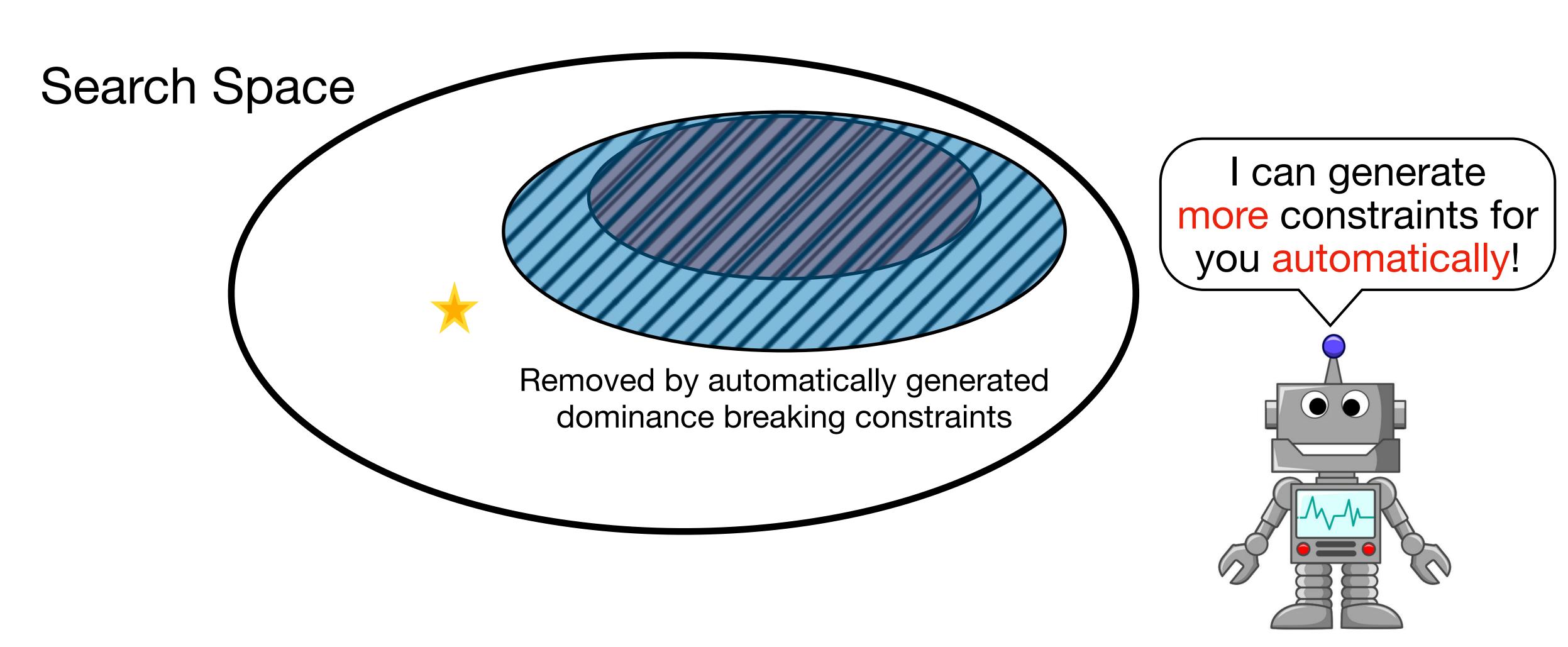
Towards More Practical and Efficient Automatic Dominance Breaking

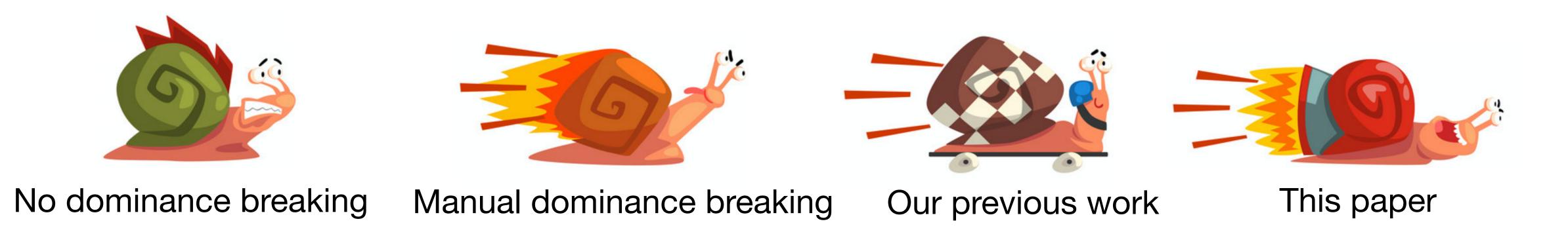
Jimmy H.M. Lee and <u>Allen Z. Zhong</u>
Department of Computer Science and Engineering
The Chinese University of Hong Kong





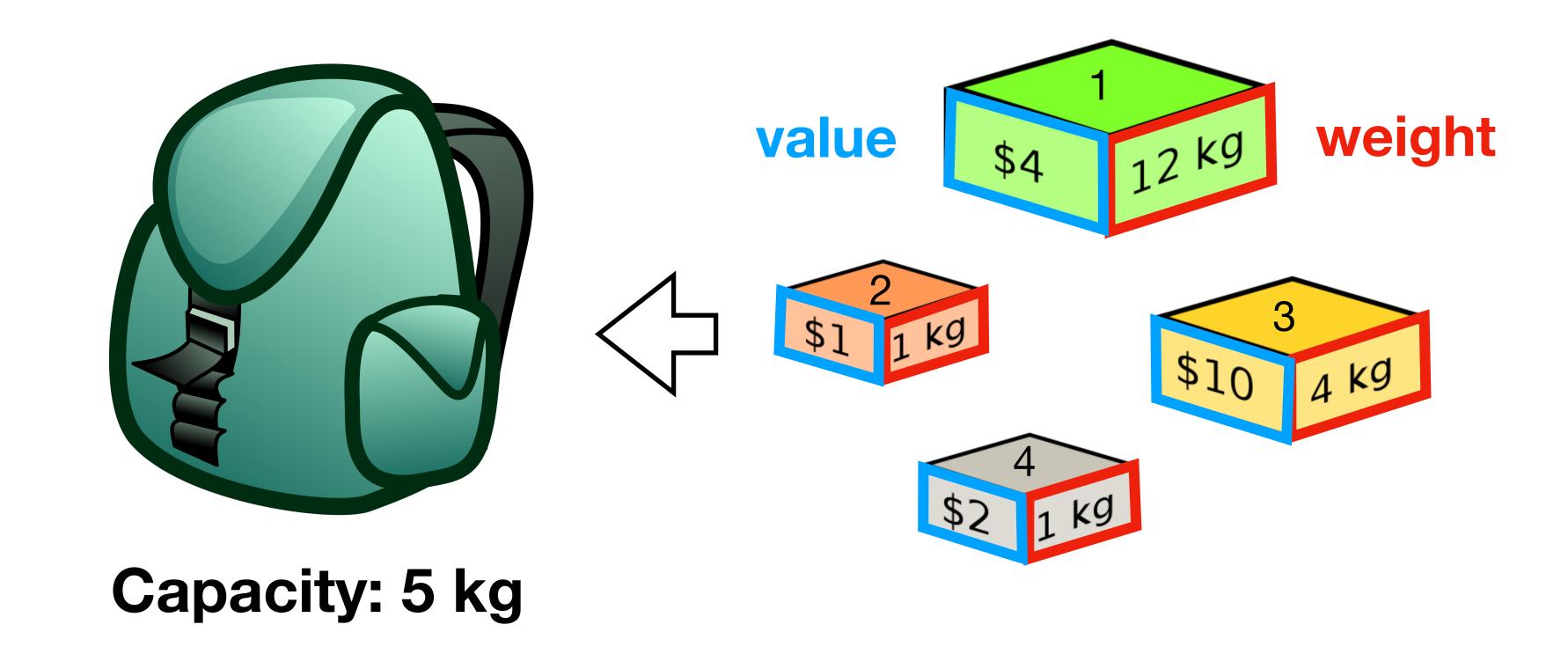
Contributions

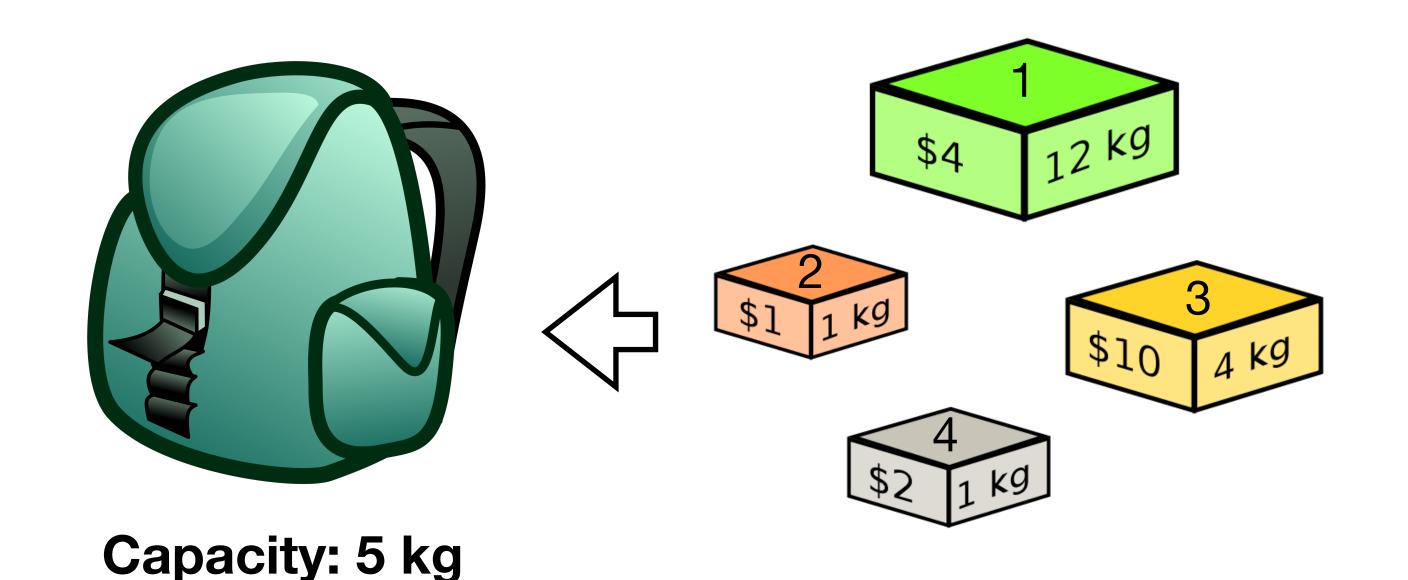
- Solving larger class of constraint optimization problems
- More efficient generation of dominance breaking constraints



Outline

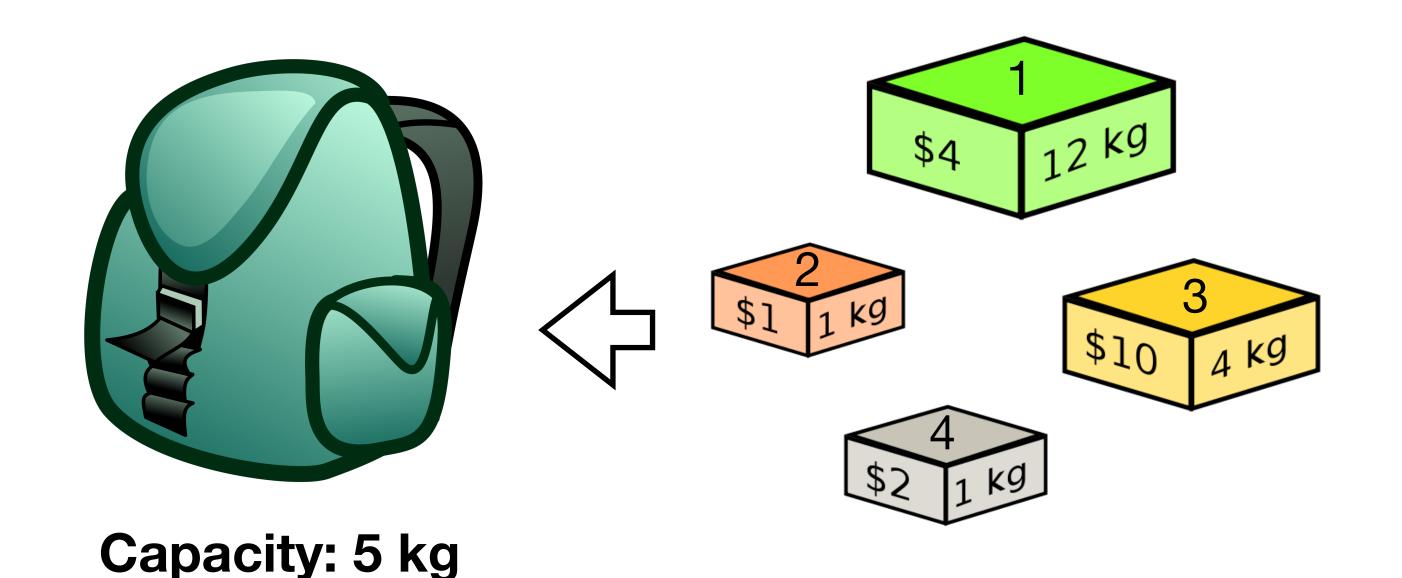
- Automatic Dominance Breaking
- Non-efficiently Checkable Constraints
- Common Assignment Elimination
- Experimental Results





$$\max 4x_1 + x_2 + 2x_3 + 10x_4$$
s.t.
$$12x_1 + x_2 + 4x_3 + x_4 \le 5$$

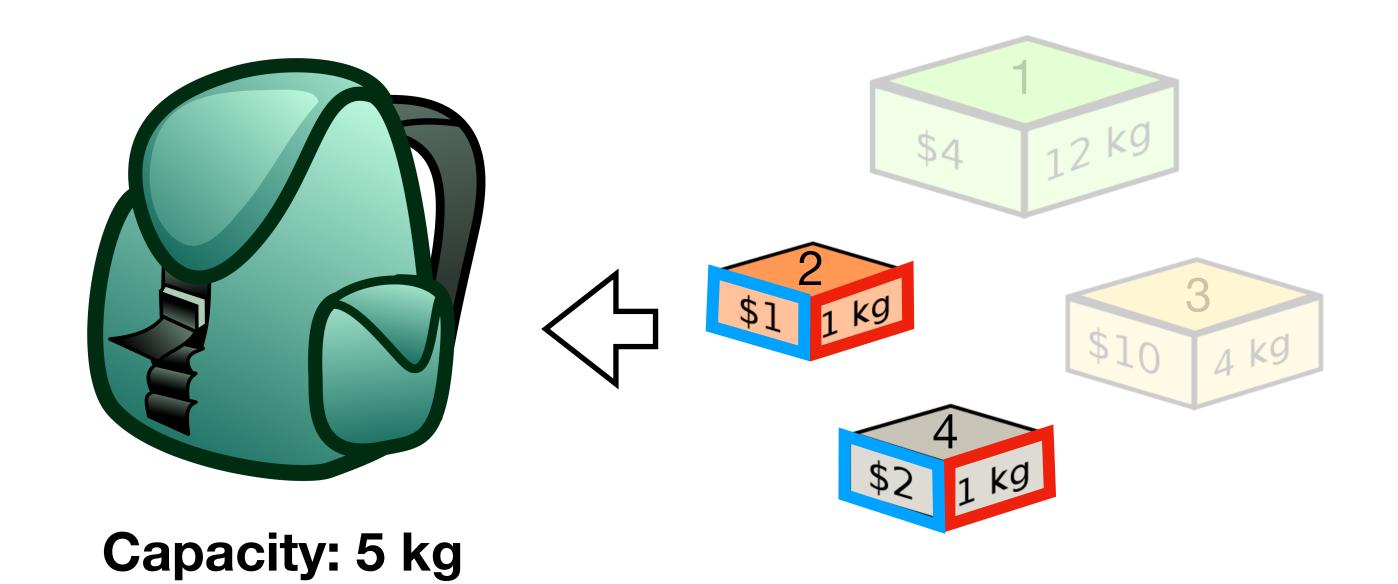
$$x_i \in \{0,1\} \text{ for } i = 1,...,4$$



$$\max 4x_1 + x_2 + 2x_3 + 10x_4$$

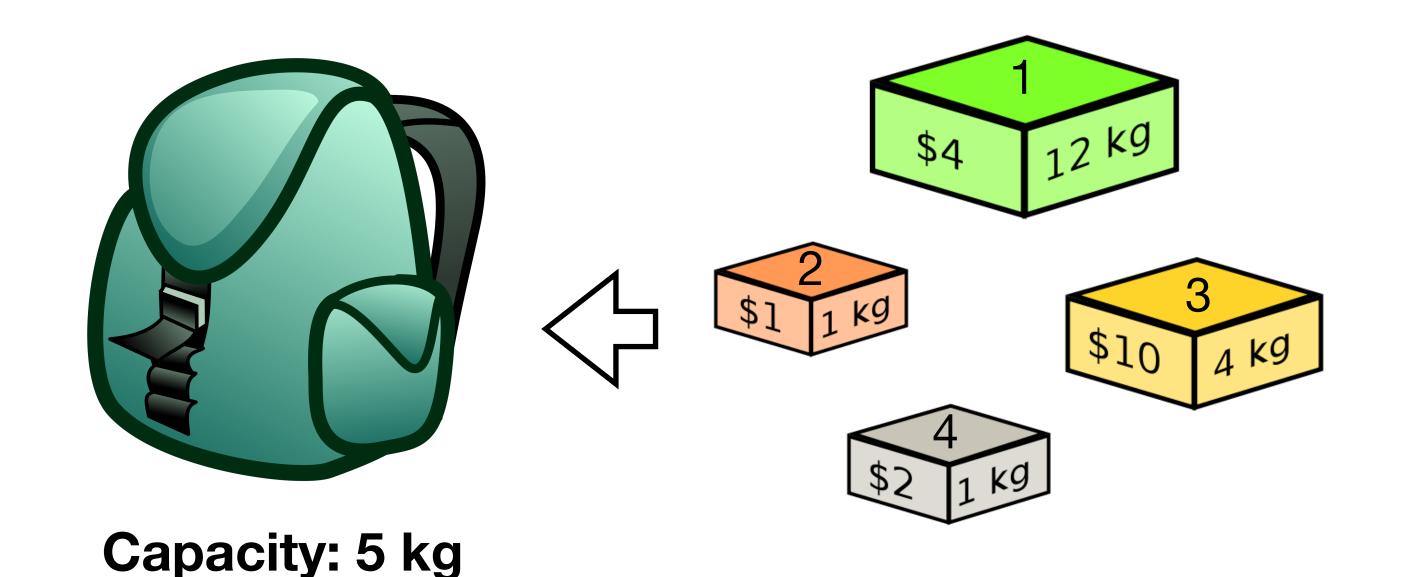
s.t.
$$12x_1 + x_2 + 4x_3 + x_4 \le 5$$

$$x_i \in \{0,1\} \text{ for } i = 1,...,4$$



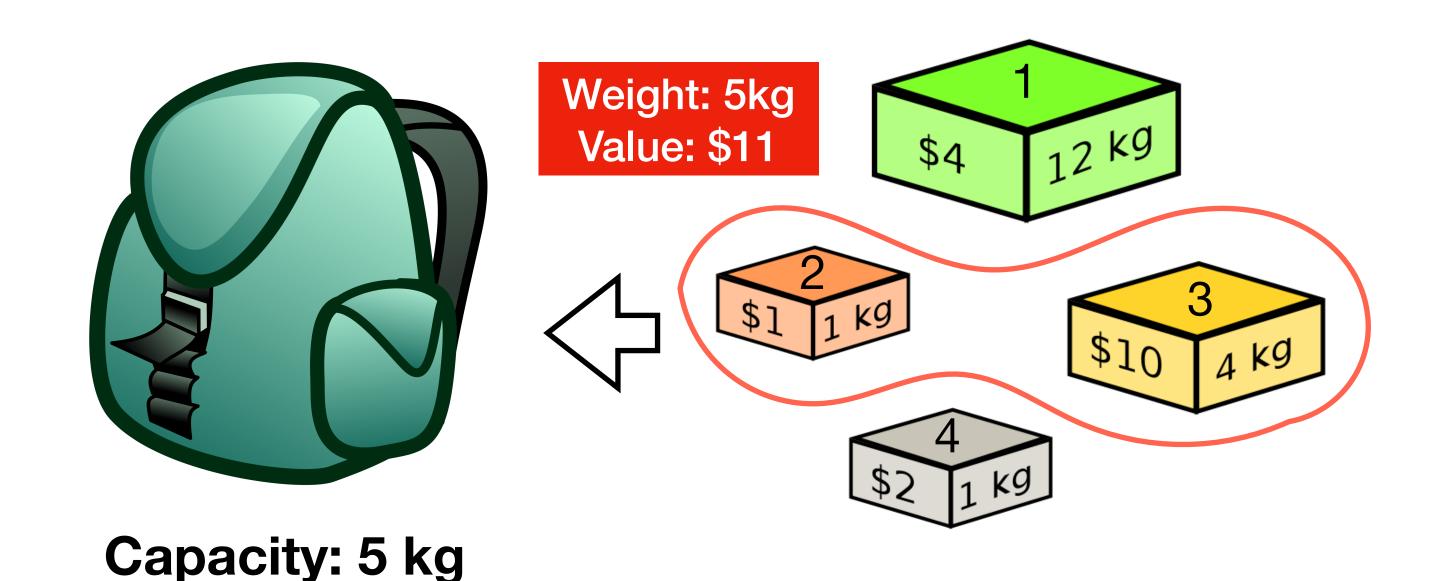
$$\max 4x_1 + x_2 + 10x_3 + 2x_4$$
s.t. $12x_1 + x_2 + 4x_3 + x_4 \le 5$

$$x_i \in \{0,1\} \text{ for } i = 1,...,4$$



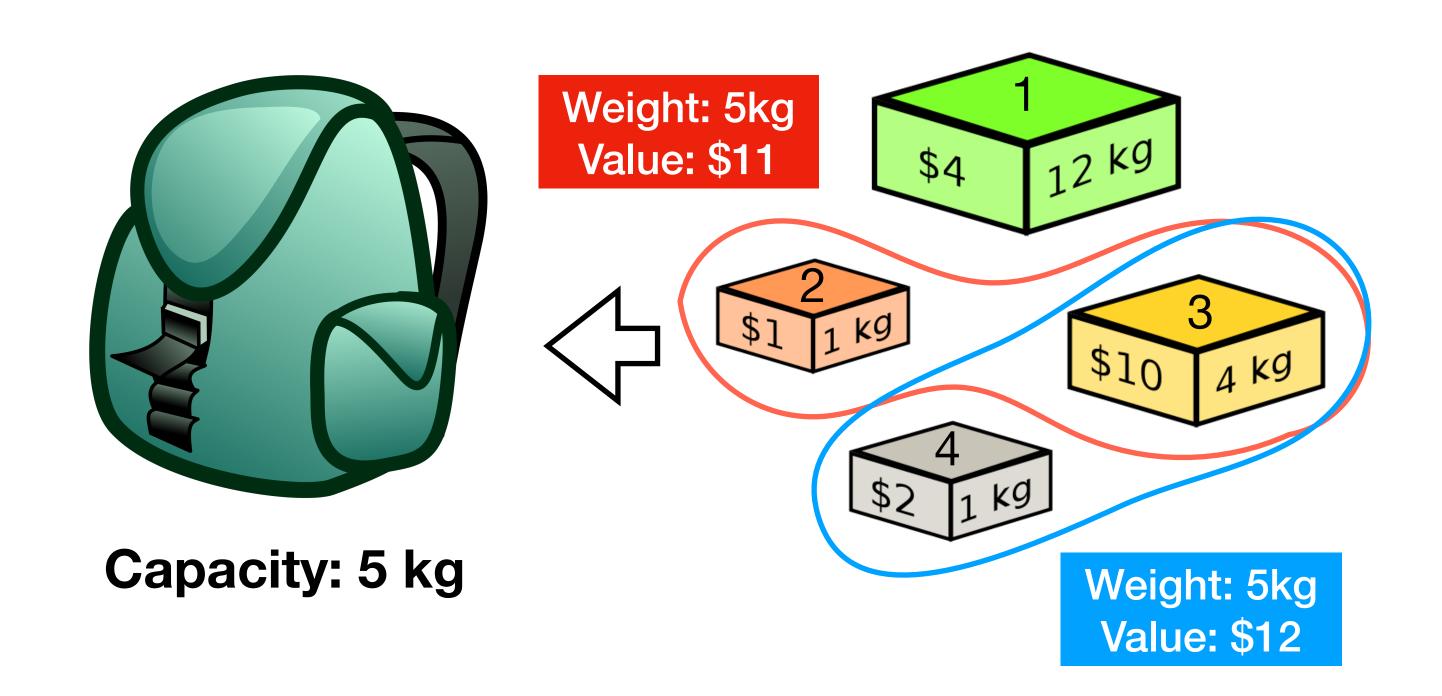
$$\max 4x_1 + x_2 + 10x_3 + 2x_4$$
s.t.
$$12x_1 + x_2 + 4x_3 + x_4 \le 5$$

$$x_i \in \{0,1\} \text{ for } i = 1,...,4$$



$$\max 4x_1 + x_2 + 10x_3 + 2x_4$$
s.t. $12x_1 + x_2 + 4x_3 + x_4 \le 5$

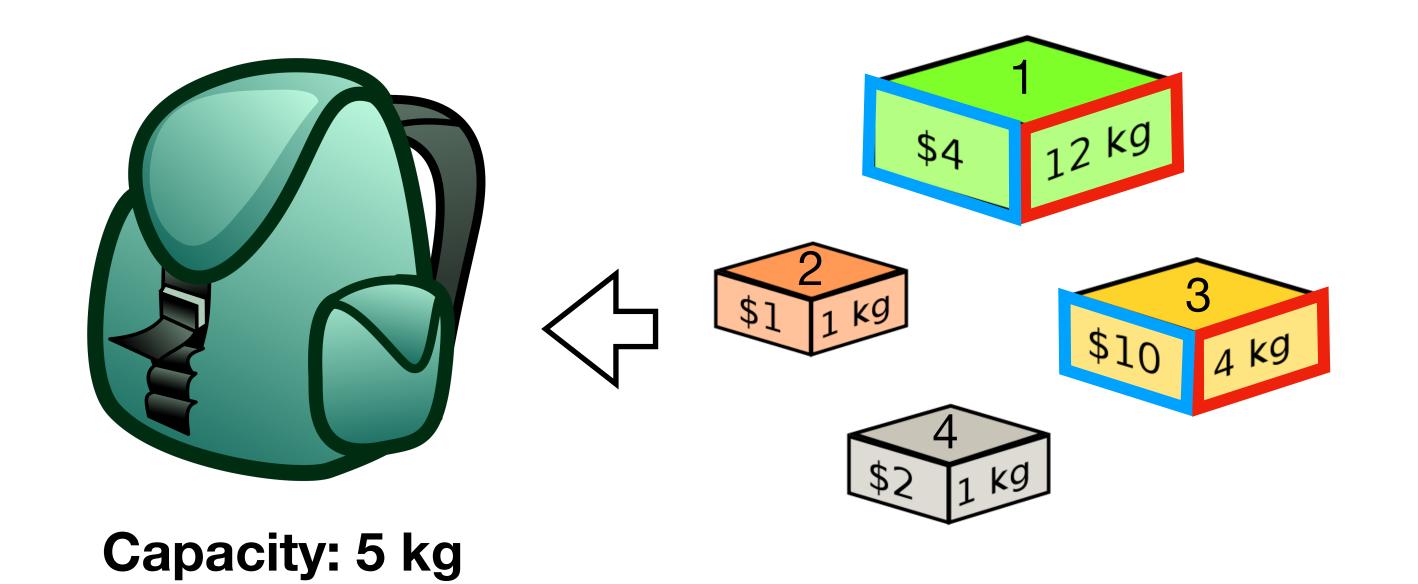
$$x_i \in \{0,1\} \text{ for } i = 1,...,4$$



$$\max 4x_1 + x_2 + 10x_3 + 2x_4$$
s.t.
$$12x_1 + x_2 + 4x_3 + x_4 \le 5$$

$$x_i \in \{0,1\} \text{ for } i = 1,...,4$$

Dominance Breaking is a useful technique for solving COPs.

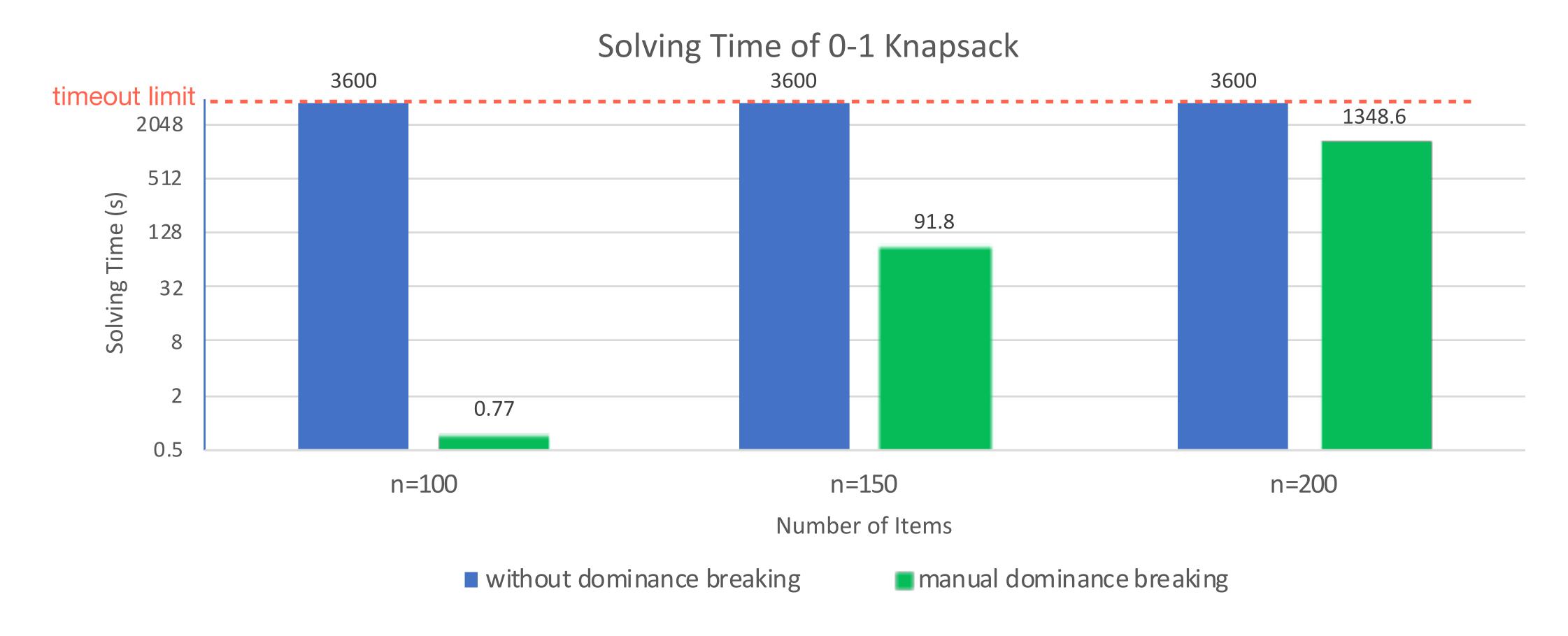


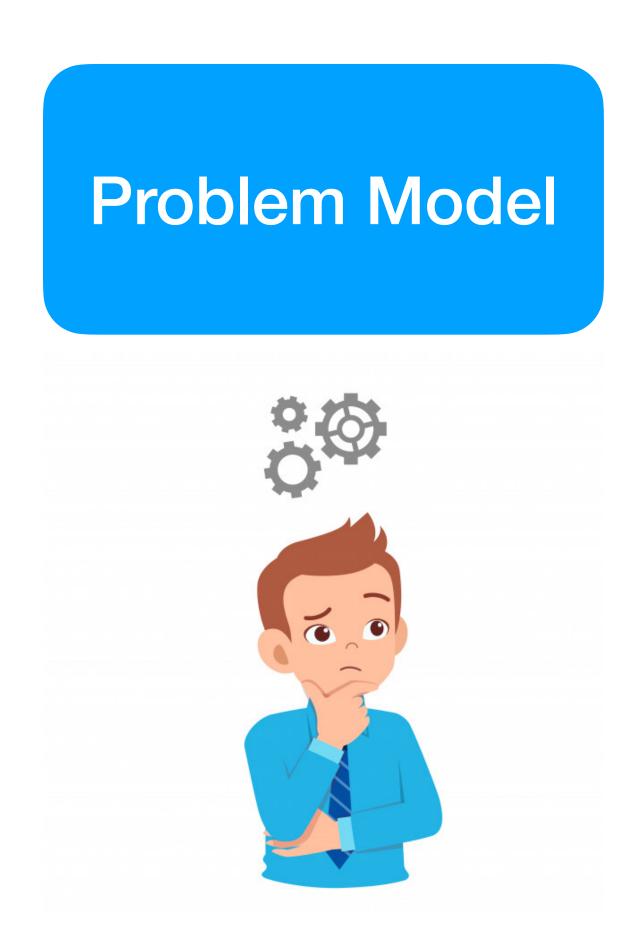
$$\max 4x_1 + x_2 + 10x_3 + 2x_4$$
s.t. $12x_1 + x_2 + 4x_3 + x_4 \le 5$

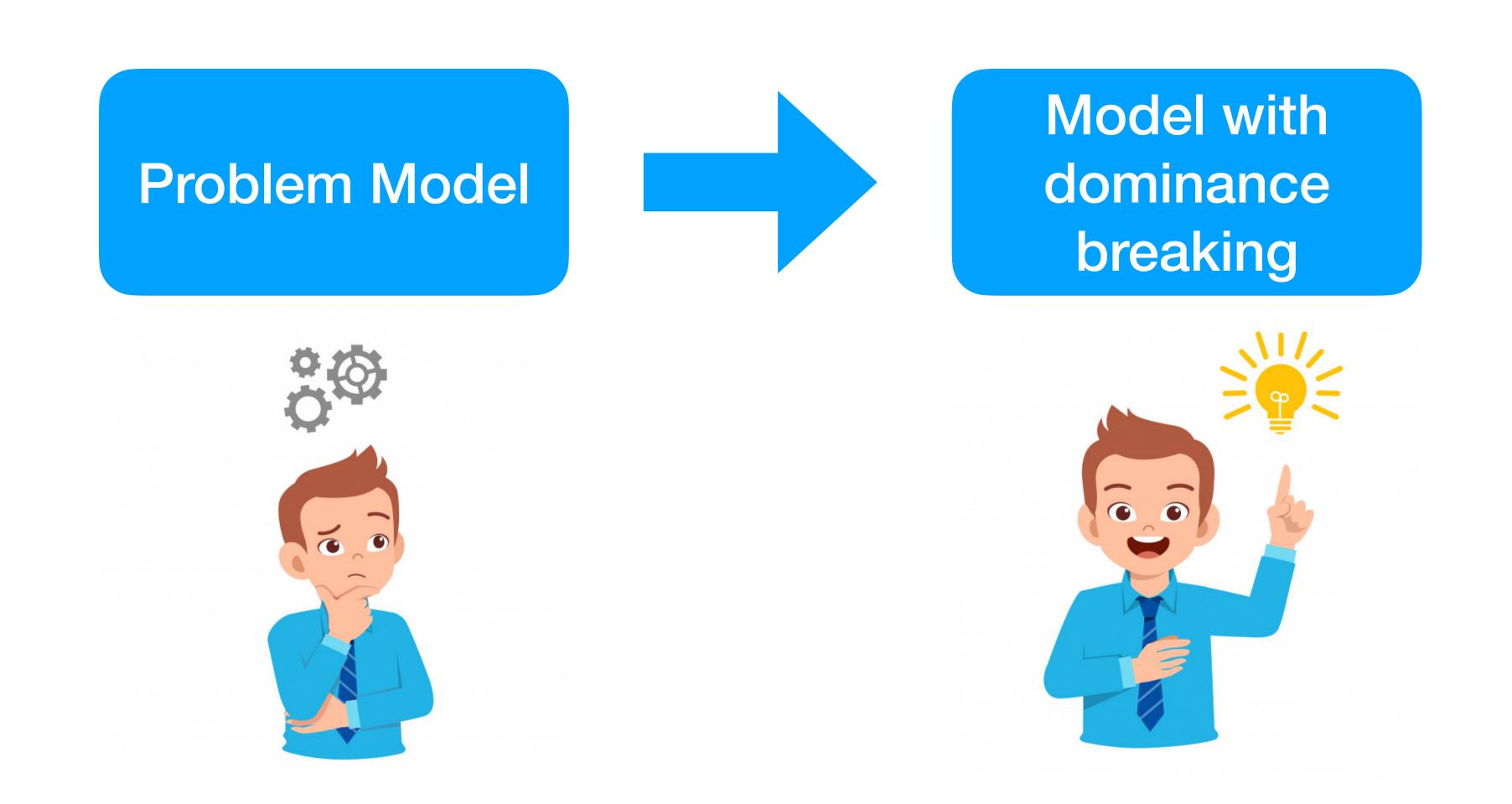
$$x_i \in \{0,1\} \text{ for } i = 1,...,4$$

$$x_2 \le x_4, x_1 \le x_3$$

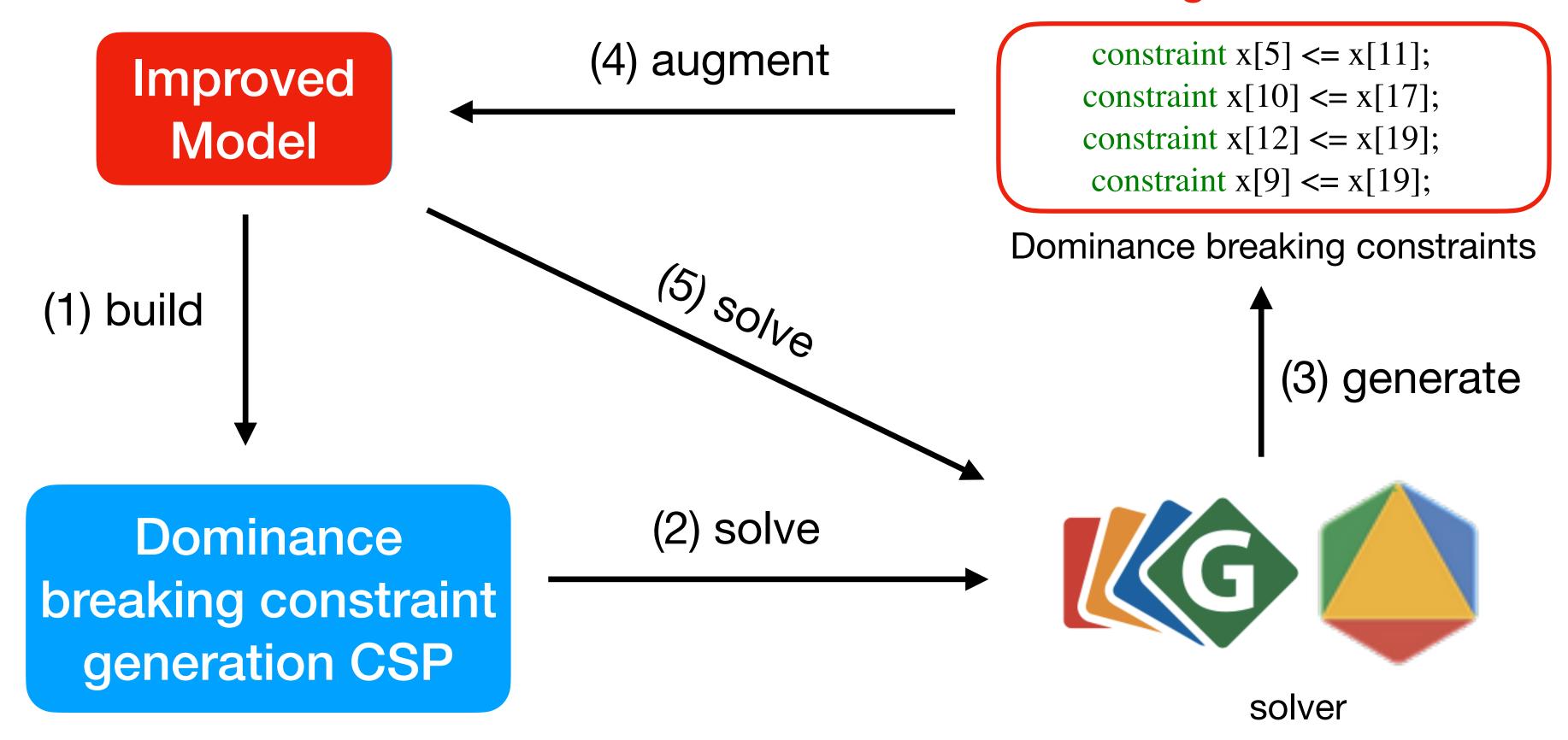
Dominance breaking constraints

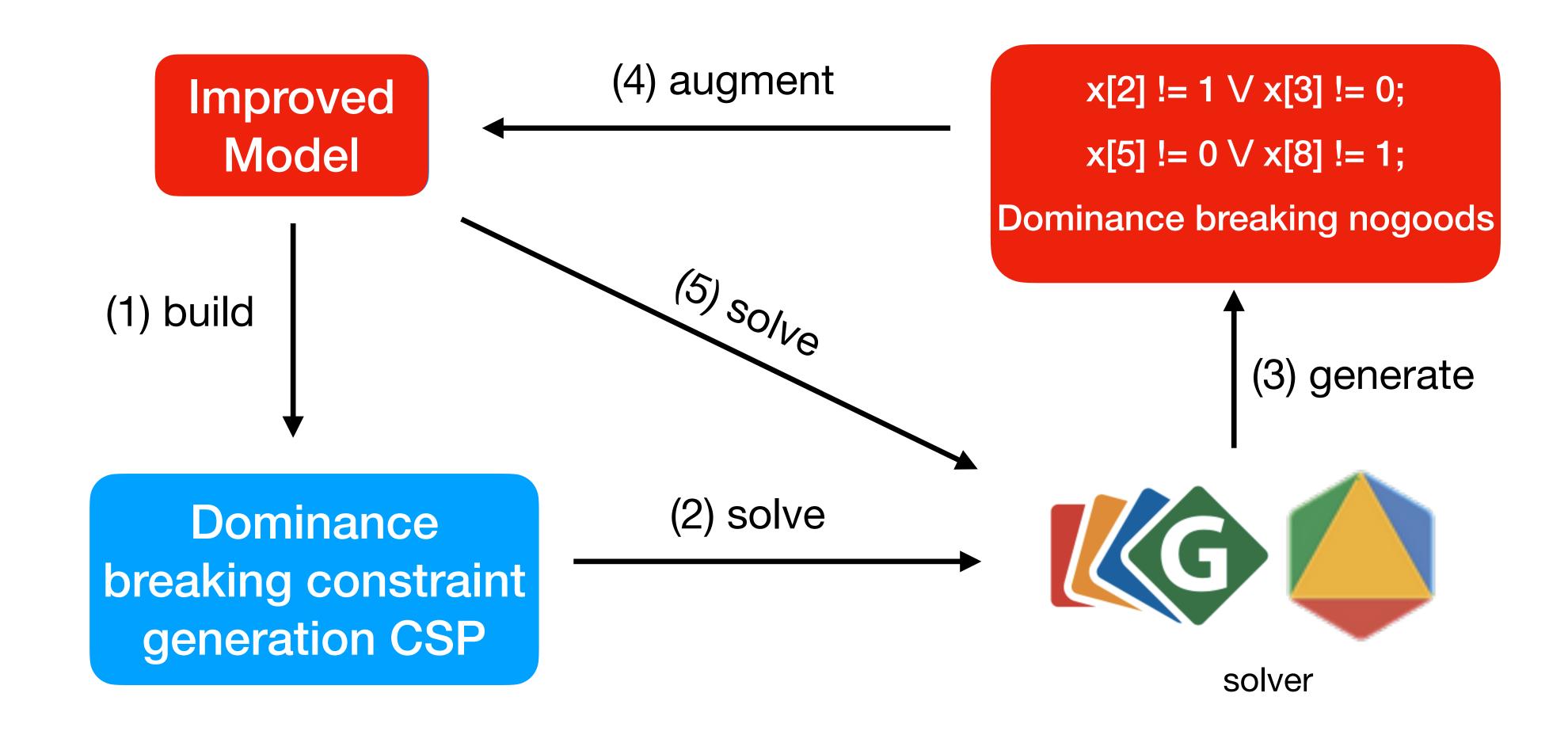


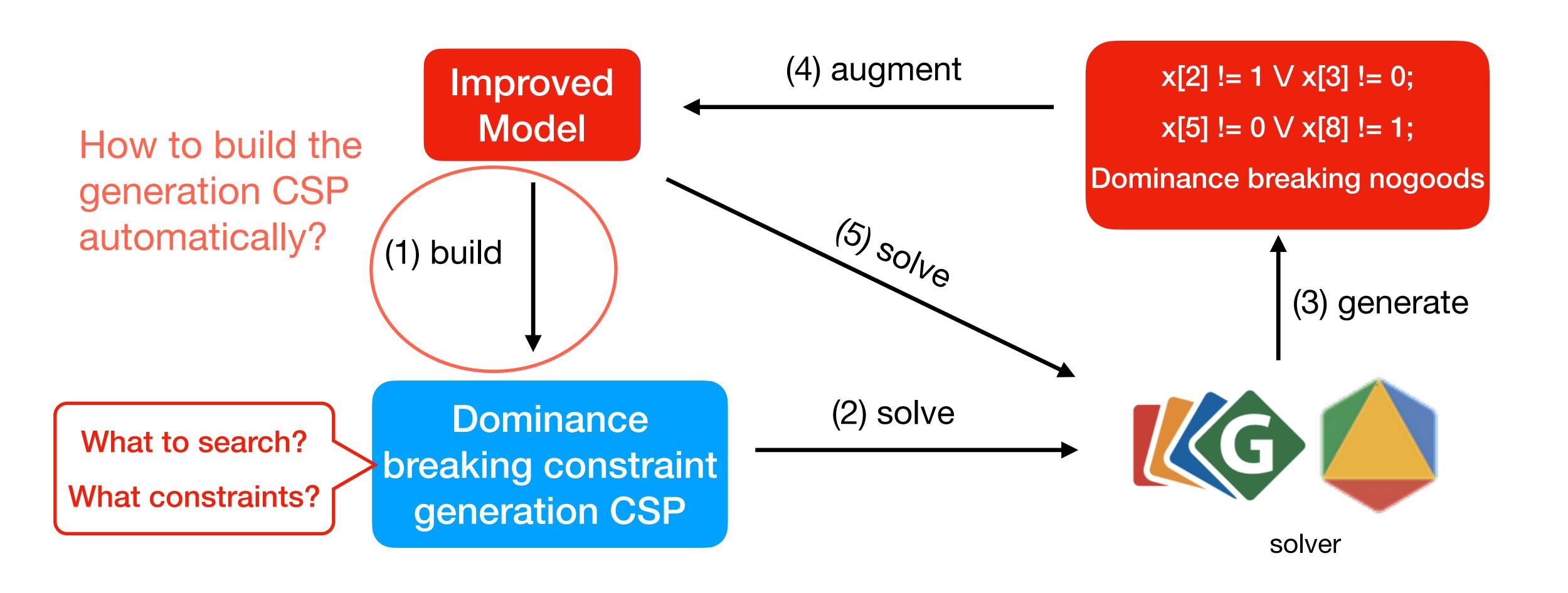




Restrict to nogood constraints only!



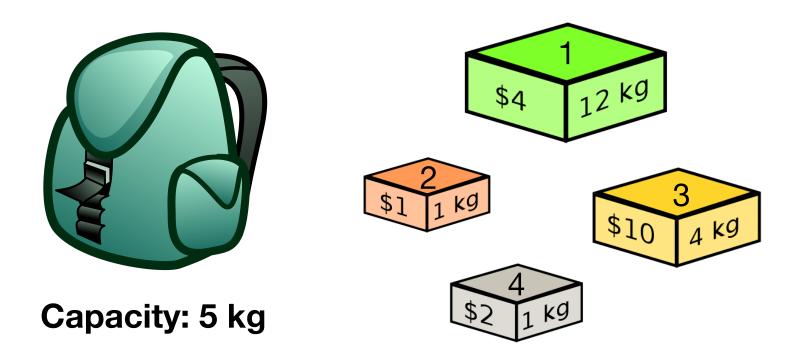




- What to search?
 - Pairs of partial assignments
- What constraints?

$$\max 4x_1 + x_2 + 10x_3 + 2x_4$$
s.t. $12x_1 + x_2 + 4x_3 + x_4 \le 5$

$$x_i \in \{0,1\} \text{ for } i = 1,...,4$$



$$\theta = \{x_2 = 0, x_4 = 1\}$$

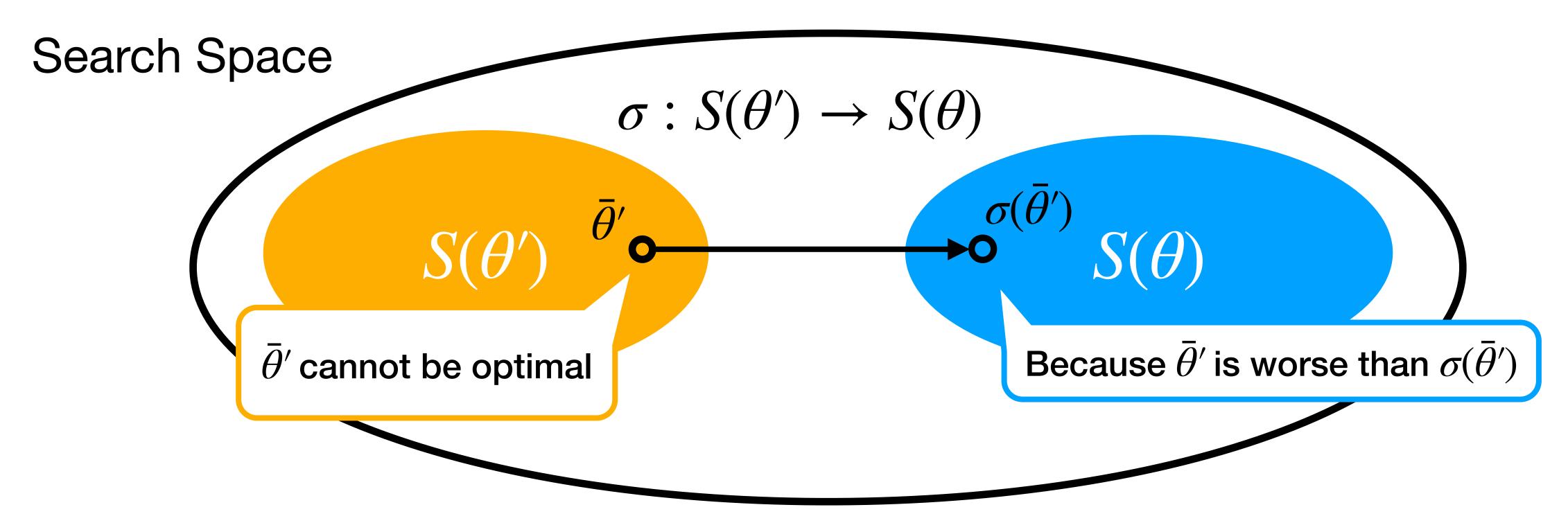
$$\theta' = \{x_2 = 1, x_4 = 0\}$$



x2	x4	x1	х3
0	1	0	0
0	1	0	1
0	1	1	0
0	1	1	1

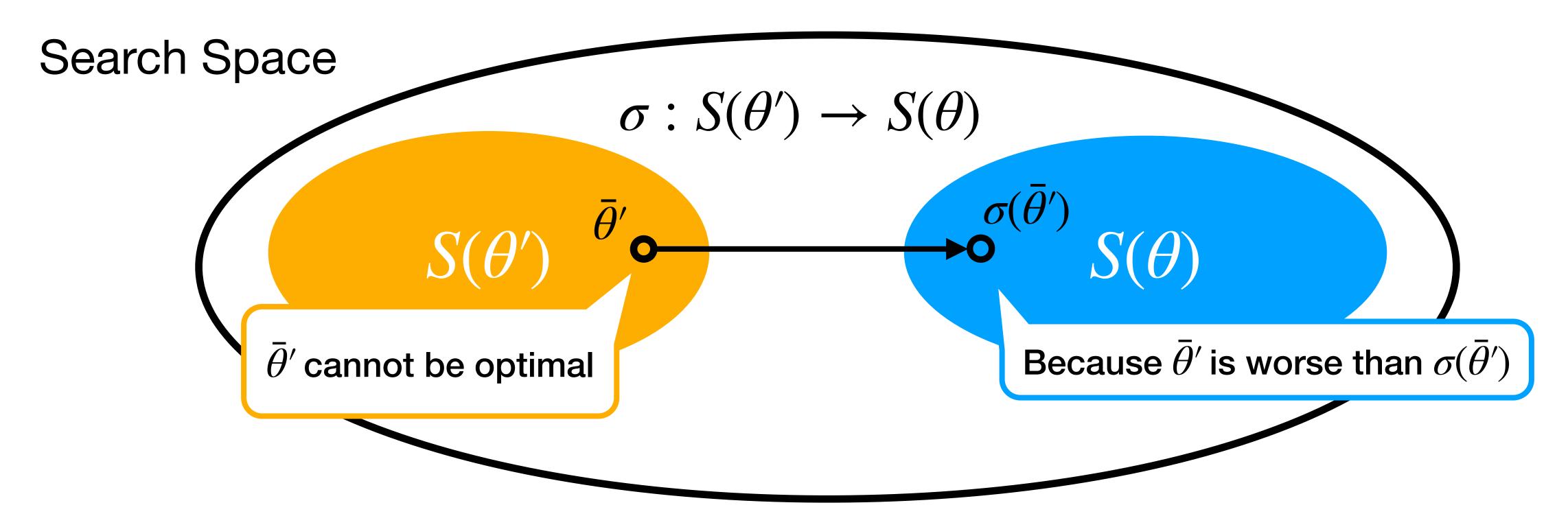
x2	x4	x1	х3
1	0	0	0
1	0	0	1
1	0	1	0
1	0	1	1

 $S(\theta')$



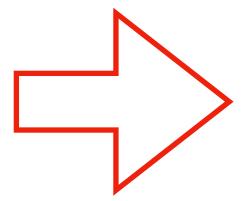
 $ar{ heta}'$ is worse than $\sigma(ar{ heta}')$ if:

- $\bar{\theta}'$ solution $\Rightarrow \sigma(\bar{\theta}')$ solution
- $f(\sigma(\bar{\theta}'))$ is better than $f(\bar{\theta}')$



 $ar{ heta}'$ is worse than $\sigma(ar{ heta}')$ if:

- Implied satisfaction
- Betterment



 $\sigma(\bar{\theta}')$ dominates $\bar{\theta}'$ ($\sigma(\bar{\theta}') < \bar{\theta}'$)

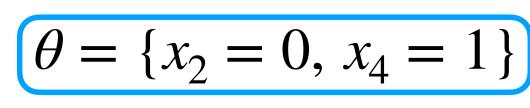
- What objects?
 - Pairs of partial assignments
- What constraints?

$$\theta' = \{x_2 = 1, x_4 = 0\}$$
equivalent
$$\theta' \equiv x_2 = 1 \land x_4 = 0$$

$$\text{negation}$$

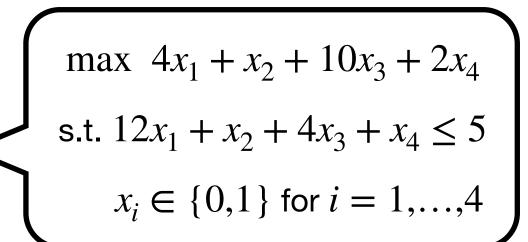
$$\neg \theta' \equiv x_2 \neq 1 \lor x_4 \neq 0$$

Dominance Breaking Nogood



x2	x4	x1	х3
0	1	0	0
0	1	0	1
0	1	1	0
0	1	1	1

$$S(\theta)$$



$$\theta' = \{x_2 = 1, x_4 = 0\}$$

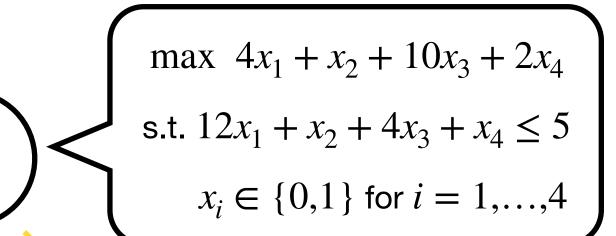
- What objects?
 - Pairs of partial assignments
- What constraints?

$$\theta = \{x_2 = 0, x_4 = 1\}$$

Theorem: if $\forall \bar{\theta}' \in S(\theta')$ s.t. $\sigma(\bar{\theta}') \prec \bar{\theta}'$, then we can add $\neg \theta'$ to P

x2	x4	x1	х3
0	1	0	0
0	_	0	1
0	1	1	0
0	1	1	1

$$S(\theta)$$



$$\theta' = \{x_2 = 1, x_4 = 0\}$$

- What objects?
 - Pairs of partial assignments
- What constraints?

Want to show : $\forall \bar{\theta}' \in S(\theta')$,

Implied satisfaction:

 $\bar{\theta}'$ solution $\Rightarrow \sigma(\bar{\theta}')$ solution

Betterment:

 $f(\sigma(\bar{\theta}'))$ is better than $f(\bar{\theta}')$

- Implied satisfaction concerns each constraint in the problem model
- Betterment concerns the objective in the problem model
- Sufficient conditions for efficiently checkable (EC) objectives and constraints

Constraints for (θ, θ') !

EC Objectives and Constraints

Objectives	Constraints	
	 Domain constraints 	
Separable objectivesSubmodular set objectivesMaximum objectives	 Boolean disjunction constraints 	
	 Linear Inequality constraints 	
	Alldifferent constraintsCircuit constraints	

Modelling

```
int: n;
          % number of items
int: W; % knapsack capacity
array [1..n] of int: w; % weight of each item
array [1..n] of int: v; % value of each item
array [1..n] of var 0..1: x;
% constraint
constraint sum (i in 1..n) (w[i]*x[i]) \leftarrow W;
% objective
solve maximize sum (i in 1..n) (v[i]*x[i]); -
```

```
% number of items
  int: n;
  int: W; % knapsack capacity
 array [1..n] of int: w; % weight of each item
 array [1..n] of int: v; % value of each item
 int: k; % length of nogoods
 array [1..k] of var 1..n: F; % indices for fixed variable
  array [1..k] of var 0..1: v1; % fixed value for \theta
  array [1..k] of var 0..1: v2; % fixed value for \theta'
 constraint increasing(F); % symmetry breaking
 % constraint for implied satisfaction
 constraint sum(t in 1..k)( w[F[t]] * v1[t] )
             \leq sum(t in 1..k)(w[F[t]] * v2[t]);
  % constraint for betterment
\rightarrow constraint sum(t in 1..k)( v[F[t]] * v1[t] )
            > sum(t in 1..k)(v[F[t]] * v2[t]);
```

Problem Model

Generation CSP Model

Modelling

```
int: n;
int: W; % knapsack capacity
array [1..n] of int: w; % weight of each item
constraint sum (i in 1..n) (w[i]*x[i]) <= W;
solve maximize sum (i in 1..n) (v[i]*x[i]);
```

```
int: n;
                                           int: W; % knapsack capacity
                                           array [1..n] of int: w; % weight of each item
                                           array [1..n] of int: v; % value of each item
                                           int: k; % length of nogoods
                                           array [1..k] of var 1..n: F; % indices for fixed variable
                                           array [1..k] of var 0..1: v1; % fixed value for \theta
                                           array [1..k] of var 0..1: v2; % fixed value for \theta'
Three Orders of magnitude improvement!
                                           constraint sum(t in 1..k)( w[F[t]] * v1[t] )
                                                     \leq sum(t in 1..k)(w[F[t]] * v2[t]);
                                        \rightarrow constraint sum(t in 1..k)( v[F[t]] * v1[t] )
                                                     > sum(t in 1..k)(v[F[t]] * v2[t]);
```

Outline

Automatic Dominance Relations

Non-Efficiently Checkable Constraints

Common Assignment Elimination

Experimental Results

```
% number of items
int: n;
int: W; % knapsack capacity
array [1..n] of int: w; % weight of each item
array [1..n] of int: v; % value of each item
array [1..n] of var 0..1: x;
% constraint
|constraint sum (i in 1..n) (w[i]*x[i]) \leq W;
constraint x[1] = 1 \land x[3] = 0 \rightarrow false;
% objective
solve maximize sum (i in 1..n) (v[i]*x[i]);
```

All constraints are efficiently checkable

A non-EC constraint

```
% number of items
int: n;
int: W; % knapsack capacity
array [1..n] of int: w; % weight of each item
array [1..n] of int: v; % value of each item
array [1..n] of var 0..1: x;
% constraint
|constraint sum (i in 1..n) (w[i]*x[i]) \leq W;
constraint x[1] = 1 \land x[3] = 0 \rightarrow false; \rightarrow var(c) = \{x_1, x_3\}
% objective
solve maximize sum (i in 1..n) (v[i]*x[i]);
```

```
% number of items
int: n;
int: W; % knapsack capacity
array [1..n] of int: w; % weight of each item
array [1..n] of int: v; % value of each item
array [1..n] of var 0..1: x;
% constraint
|constraint sum (i in 1..n) (w[i]*x[i]) \leq W;
constraint x[1] = 1 \land x[3] = 0 \rightarrow false;
% objective
solve maximize sum (i in 1..n) (v[i]*x[i]);
```

 C_{nec} : the set of non-EC constraints

Constraints in the generation CSP

- Sufficient conditions for EC constraints and objectives
- $\forall c \in C_{nec}$ s.t. $var(\theta) \cap var(c) = \emptyset$

```
int: n;
          % number of items
         % knapsack capacity
int: W;
array [1..n] of int: w; % weight of each item
array [1..n] of int: v; % value of each item
array [1..n] of var 0..1: x;
% constraint
|constraint sum (i in 1..n) (w[i]*x[i]) \leq W;
constraint x[1] = 1 \land x[3] = 0 \rightarrow false;
% objective
solve maximize sum (i in 1..n) (v[i]*x[i]);
```

 C_{nec} : the set of non-EC constraints

Constraints in the generation CSP

Sufficient conditions for EC constraints and objectives

Theorem: if $var(\theta) \cap var(c) = \emptyset$, then (θ, θ')

satisfies implied satisfaction for c

```
% number of items
int: n;
int: W; % knapsack capacity
array [1..n] of int: w; % weight of each item
array [1..n] of int: v; % value of each item
array [1..n] of var 0..1: x;
% constraint
|constraint sum (i in 1..n) (w[i]*x[i]) \leq W;
constraint x[1] = 1 \land x[3] = 0 \rightarrow false;
% objective
solve maximize sum (i in 1..n) (v[i]*x[i]);
```

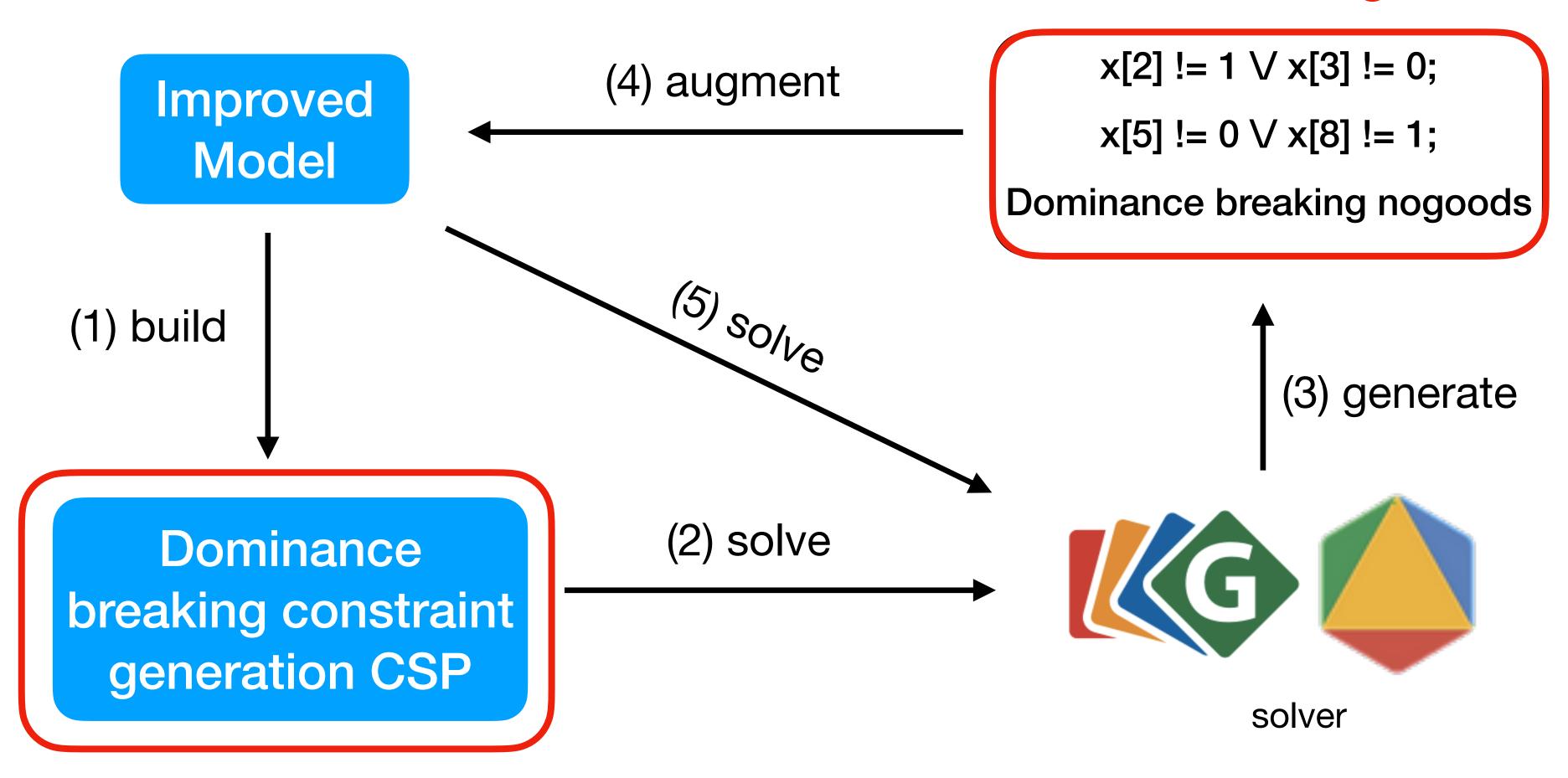
- Useful only if the scope of the non-EC constraint is relatively small
 - Side constraints that involves several variables
- Enable automatic dominance breaking on a larger class of problems

Outline

- Automatic Dominance Relations
- Non-efficiently Checkable Constraints
- Common Assignment Elimination
- Experimental Results

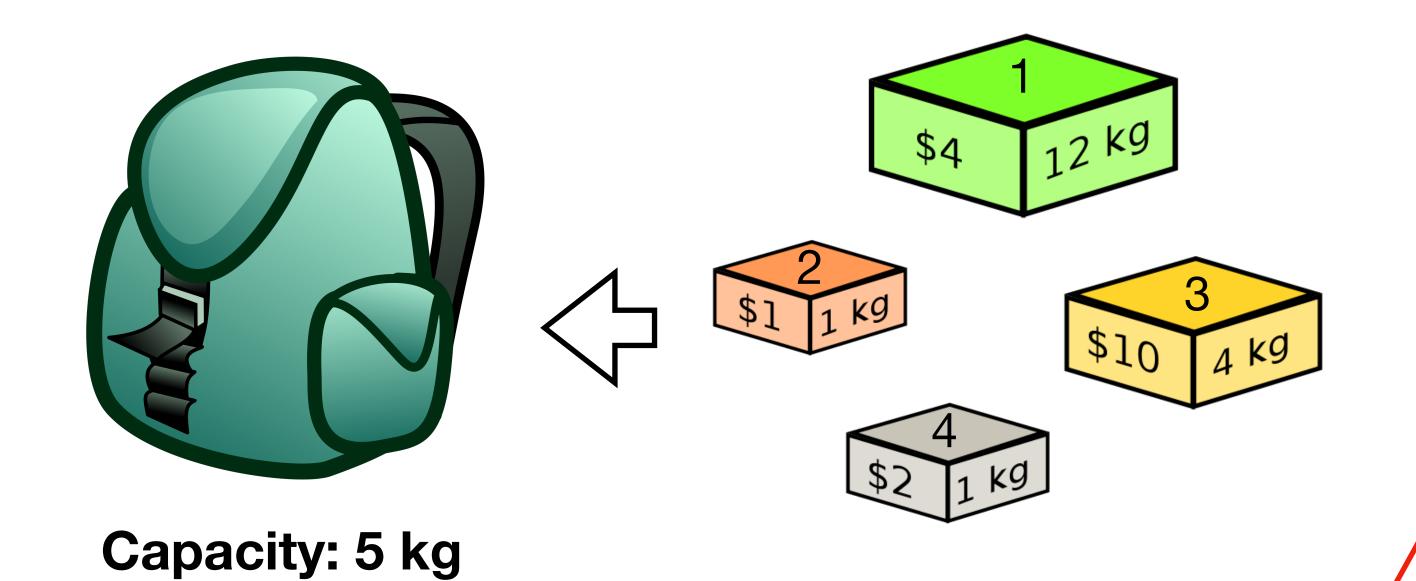
Motivation

Redundant Nogoods!



Too time-consuming!

Common Assignment Elimination



How to avoid generating c_1 ? Adding more constraints!

$$\max 4x_1 + x_2 + 10x_3 + 2x_4$$
s.t. $12x_1 + x_2 + 4x_3 + x_4 \le 5$

$$x_i \in \{0,1\} \text{ for } i = 1,...,4$$

$$\equiv (x_2 \ne 1 \lor x_4 \ne 0 \lor x_5 \ne 1)$$

$$c_2 \equiv (x_2 \ne 1 \lor x_4 \ne 0)$$

$$c_2 \Rightarrow c_1$$

Common Assignment Elimination

Generation CSP

• $var(\theta) = var(\theta')$

Generate

• $\forall \bar{\theta}' \in S(\theta') \text{ s.t. } \sigma(\bar{\theta}') \prec \bar{\theta}'$

• $\bar{\theta}'$ solution $\Rightarrow \sigma(\bar{\theta}')$ solution

 $f(\sigma(\bar{\theta}'))$ is better than $f(\bar{\theta}')$



$$\theta_1 = \{x_2 = 0, x_4 = 1, x_3 = 1\}$$
 $\theta_1' = \{x_2 = 1, x_4 = 0, x_3 = 1\}$

Common

assignment

Eliminate
$$(x_3 = 1)$$

$$\theta_2 = \{x_2 = 0, x_4 = 1\}$$
 $\theta_2' = \{x_2 = 1, x_4 = 0\}$

$$\theta_1 \prec \theta_1' \downarrow \text{Derive}$$

$$\theta_2 < \theta_2'$$
? Derive

$$c_2 \equiv \neg \theta_2' \equiv (x_2 \neq 1 \lor x_4 \neq 0)$$

 $\frac{c_1 = -c_1 = (x_2 \neq 1 \lor x_4 \neq 0 \lor x_3 \neq 1)}{\mathsf{Redundant}}$

Common Assignment Elimination

Generation CSP

- $var(\theta) = var(\theta')$
- $\forall \bar{\theta}' \in S(\theta') \text{ s.t. } \sigma(\bar{\theta}') \prec \bar{\theta}'$
 - $\bar{\theta}'$ solution $\Rightarrow \sigma(\bar{\theta}')$ solution
 - $f(\sigma(\bar{\theta}'))$ is better than $f(\bar{\theta}')$ $(x_3 = 1) \notin \theta \cap \theta'$



$$\theta_2 = \{x_2 = 0, x_4 = 1\}$$
 $\theta_2' = \{x_2 = 1, x_4 = 0\}$

$$\theta_2 \prec \theta_2'$$
? Derive

$$c_2 \equiv \neg \theta_2' \equiv (x_2 \neq 1 \lor x_4 \neq 0)$$

Commonly Eliminable Assignments

Common Assignments	Objectives / Constraints
x = 0	 Submodular set objectives
	 Boolean disjunction constraint
x = v for any value v	 Separable objectives
	 Domain constraint
	 Linear Inequality constraint
	Alldifferent constraint

Modelling

```
int: n;
          % number of items
int: W; % knapsack capacity
array [1..n] of int: w; % weight of each item
array [1..n] of int: v; % value of each item
array [1..n] of var 0..1: x;
% non-EC constraint
|constraint x[3] != 1 \lor x[1] != 0;
% EC constraint
constraint sum (i in 1..n) (w[i]*x[i]) \leftarrow W;
% objective
solve maximize sum (i in 1..n) (v[i]*x[i]);
```

```
% problem parameters
int: k; % length of partial assignments
array [1..k] of var 1..n: F; % indices for fixed variable
array [1..k] of var 0..1: v1; % fixed value for \theta
array [1..k] of var 0..1: v2; % fixed value for \theta'
constraint increasing(F); % symmetry breaking
% constraint for implied satisfaction and betterment
```

Problem Model

Generation CSP Model

Modelling

```
int: n;
          % number of items
int: W; % knapsack capacity
array [1..n] of int: w; % weight of each item
array [1..n] of int: v; % value of each item
array [1..n] of var 0..1: x;
% non-EC constraint
|constraint x[3] != 1 \lor x[1] != 0;
% EC constraint
constraint sum (i in 1..n) (w[i]*x[i]) \leftarrow W;
% objective
solve maximize sum (i in 1..n) (v[i]*x[i]);
```

```
% problem parameters
int: k; % length of partial assignments
array [1..k] of var 1..n: F; % indices for fixed variable
array [1..k] of var 0..1: v1; % fixed value for \theta
array [1..k] of var 0..1: v2; % fixed value for \theta'
constraint increasing(F); % symmetry breaking
% constraint for implied satisfaction and betterment
% handling non-EC constraint
constraint formal (i in 1..k) (F[i] != 3 \lor F[I] != 1);
```

Problem Model

Generation CSP Model

Modelling

```
int: n;
          % number of items
         % knapsack capacity
int: W;
array [1..n] of int: w; % weight of each item
array [1..n] of int: v; % value of each item
array [1..n] of var 0..1: x;
% non-EC constraint
|constraint x[3] != 1 \lor x[1] != 0;
% EC constraint
constraint sum (i in 1..n) (w[i]*x[i]) <= W;
% objective
solve maximize sum (i in 1..n) (v[i]*x[i]);
```

```
% problem parameters
int: k; % length of partial assignments
array [1..k] of var 1..n: F; % indices for fixed variable
array [1..k] of var 0..1: v1; % fixed value for \theta
array [1..k] of var 0..1: v2; % fixed value for \theta'
constraint increasing(F); % symmetry breaking
% constraint for implied satisfaction and betterment
% handling non-EC constraint
constraint formal (i in 1..k) (F[i] != 3 \lor F[I] != 1);
% common assignment elimination
constraint formal (i in 1..k, v in 0..1) (
      v1[k] != v \lor v2[k] != v
```

Problem Model

Generation CSP Model

Outline

- Automatic Dominance Relations
- Non-efficiently Checkable Constraints
- Common Assignment Elimination
- Experimental Results

Experimental Setup

- MiniZinc for modelling, Chuffed for solving;
- Two hours total timeout; One hour timeout for no-good generation;
- 6 benchmarks, 20 random instances for each configuration
 - Existing: Knapsack, Disjunctively Constrained Knapsack, Concert Hall Scheduling, Maximum Cut
 - KnapsackSide: Knapsack with additional table constraints
 - PCBoard: larger overhead of nogood generation

Experimental Evaluation







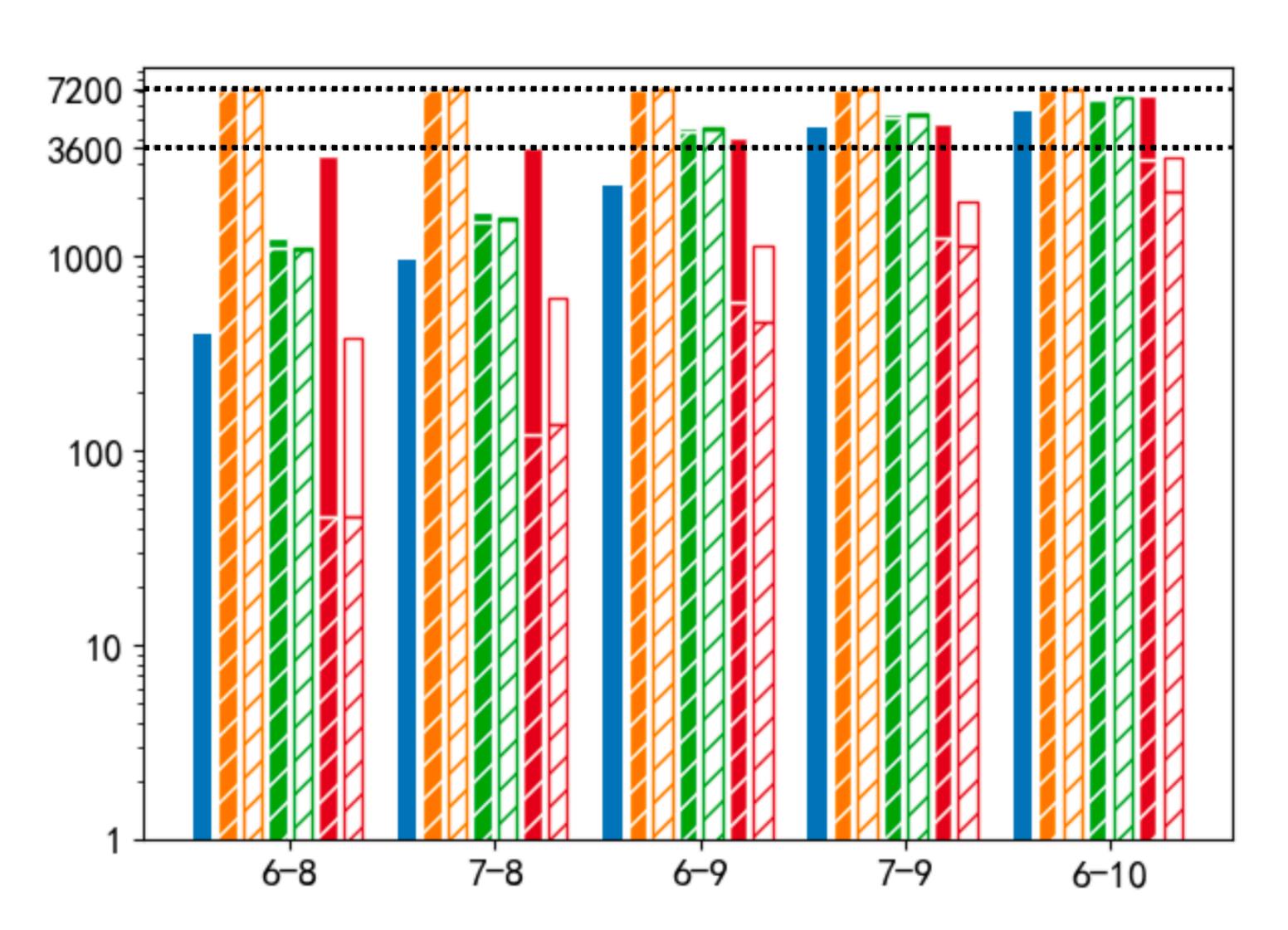












Concluding Remarks

- Dominance breaking is powerful, but applying it is difficult.
- Automatic dominance breaking for a class of problems.
 - Instead of free-form constraints, generate nogoods
 - Some are not discovered by human (yet)
- Handle Non-EC constraints and Common Assignment Elimination

Thanks for listening!